# The performance of ultrasonic pulse velocity on the prediction of tensile granite behaviour: a study based on artificial neural networks

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**ABSTRACT:** The rehabilitation and repair of existing structures requires inspection. This generally includes in situ non-destructive testing. A very economical test is the non-destructive ultrasonic pulse velocity test (UPV). Lower information is available in the literature in relation to the use of this technique for the estimation of the tensile strength of materials. Therefore, this paper aims at using artificial neural networks (ANN) in the prediction of the mechanical behaviour of granites under tensile loading. The parameters under analysis are the tensile strength, displacement at peak stress and critical crack opening. For this, experimental results obtained from the physical and mechanical characterization under tension of distinct types of granites are combined and the performance of the developed models using the UPV index alone and combined with other physical parameters is analysed. The results of the ANN models are also compared with respect to the results of regression models. The criteria used to evaluate the predictive performances of the models were the coefficient of correlation (R) and root mean square error (RMSE).

*Keywords: granite, tensile strength, ultrasonic pulse velocity, artificial neural networks*

## NOTATION

*ANN* artificial neural network; $f_t$ tensile strength; *LVDT* linear variable displacement transducer; *UPV* ultrasonic pulse velocity; $w_c$ critical crack opening; $\delta_{ft}$ displacement peak stress

## 1 INTRODUCTION

Nowadays there is a growing concern regarding the preservation of ancient monuments, many of which are built in stone. Generally, non-destructive testing is used to assess the degree of deterioration of the stones. Among other tests, the ultrasonic velocity tests are those most used. Therefore, many correlations between the ultrasonic velocity and other physical and mechanical parameters are presented in the specialized bibliography.

In Portugal, and particularly in the north region, there are many monuments built with granite. That’s why this paper includes granites and aims at establishing relationships between ultrasonic pulse velocity (UPV) and other properties of granite that best define its tensile behaviour. These properties are tensile strength ($f_t$), displacement at peak stress ($\delta_{ft}$) and critical crack opening ($w_c$). Models using artificial neural networks (ANN) are also developed. For this, experimental results obtained from the physical and mechanical characterization under tension of distinct types of granites

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are combined and the performance of using the UPV index alone and combined with other physical parameters (porosity, η, and dry density, ρ) in the prediction of key parameters defining the complete tensile behaviour of granites is analysed.

Many authors have been used ultrasonic pulse velocity applied to artificial intelligent techniques (AIT) to predict physical and mechanical characteristics of rocks, being the ANN the most used. However, Support Vector Machines (SVM) and Genetic Programming (GP) have also been used. Çanakci, H. and Pala [1] obtained a formula based on ANN for the determination of tensile strength of Turkish basalt based on ultrasonic pulse velocity, dry density and water absorption parameters. They obtained good results and their formula showed good generalization. Baykasoglu et al. [2] applied a set of genetic programming techniques to the uniaxial compressive strength (UCS) and tensile strength prediction of chalky and clayey soft limestone from Turkish Gaziantep region. They used as input parameters ultrasonic pulse velocity, water absorption, dry density, saturated density and bulk density. It is claimed the ability of genetic programming techniques to provide good prediction equations for strength forecast. Gokceoglu et al. [3] constructed weathering degree prediction models of granites with artificial neural networks and fuzzy inference systems. Model inputs were porosity, P-wave velocity and uniaxial compressive strength. According to them the developed models exhibited high prediction performances and can be used for indirect determination of weathering degree. Dehghan et al. [4] used regression analysis and ANN to predict the uniaxial compressive strength and modulus of elasticity of Travertine samples. The P-wave velocity, the point load index, the Schmidt hammer rebound number and porosity were used as inputs for both methods. The ANN models had two outputs, namely modulus of elasticity, E, and uniaxial compression strength, UCS. Karakus [5] developed three genetic programming models to establish the relationship between granitic rock properties collected from different regions in Turkey. The first model builds up a function for modulus of elasticity using UCS, total porosity, sonic velocity-$v_p$, point load index and Schmidt Hammer value. Second and third models derived functions for uniaxial compressive and tensile strength of granitic rocks using total porosity, sonic velocity, point load index and Schmidt Hammer values. All the generated models showed a good prediction capacity. Martins et al. [6] applyed multiple regressions (MR), ANN and SVM to predict the UCS and the deformation modulus of the Oporto granite. They used a database containing 55 rock sample records which contains the values of free porosity ($N_{48}$), dry bulk density, ultrasonic velocity, UCS and the modulus of elasticity. All the models have good predictive capacities. However, the best forecasting capacity was obtained with the SVM model with $N_{48}$ and UPV as input parameters. Yesiloglu-Gultekin et al. [7] used non-linear multiple regression, ANN and adaptive-neurofuzzy inference system (ANFIS) to predict the UCS of various granitic rocks selected from Turkey. Three different models were constructed based on two input parameters. One model with the tensile strength and P-wave velocity, other with block punch index test (BPI) and P-wave velocity, and another with the point load index test (Is(50)) and P-wave. The ANFIS was the best predictive tool. The model that includes tensile strength and P-wave velocity data was the best for estimating UCS. Mishra and Basu [8] presented regression analyses and fuzzy inference system (FIS) in predicting UCS of granite, schist and sandstone using as input variables indices such as block punch index, point load strength, Schmidt rebound hardness, ultrasonic P-wave velocity, and physical properties (effective porosity and density). Both MR analyses and the FIS exhibited good performances. Nevertheless, according to the authors, FIS model is a more competent analysis technique than the MR model because of its efficacy in dealing with uncertainties and impreciseness in the test results with transparency and accuracy. Yurkadul and Akdas [9] used ANN for the development of a model that predicts the UCS of natural building stones corresponding to 37 different carbonate rock samples. UPV, Schmidt hammer hardness and Shore hardness were used as input parameters. Developed models using only one input parameter or their combinations showed good performances. Kumar et al. [10] developed ANN and multiple nonlinear regression models to predict rock properties. Drill bits peed, penetration rate, drill bit diameter and equivalent sound level produced during drilling were used as input parameters. The developed models allow the prediction of UCS, Schmidt rebound number, dry density, P-wave velocity, tensile strength, modulus of elasticity and percentage porosity. All of these parameters are simultaneously the output of the ANN models. It was concluded that, in general, the ANN and multiple regressions lead to similar results and are efficient in predicting rock properties from sound levels produced during drilling. Beiki et al. [11] developed prediction models for estimating UCS and elasticity modulus of carbonate rocks in Iran using GP and regression. Porosity, density, and P-wave velocity were used as input parameters. Both MR models and GP models have reasonable prediction capacities. However, GP models have better performance than multiple regression models.

The overview on the use of the AIT shows that the prediction of mechanical properties of rock materials is much focused on the prediction of the compressive strength and very few studies are available in the scope of the prediction of tensile strength. Thus, this paper has as the main goal to provide information about the use of the ANN for the prediction of the main parameters describing the tensile behaviour of granites based on the results of an extensive experimental campaign carried out on distinct types of granites.

## 2 OVERALL BEAVIOUR OF THE GRANITE IN TENSION

Granite is the most used stone in the construction of ancient buildings, ornamental elements and movable stone heritage artifacts (e.g. statues, altar pieces, benches, etc.) in the North of Portugal, either in monumental or vernacular architecture. A wide range of granitic rocks is present in masonry buildings and artifacts, depending on their petrographic features, such as grain size and internal texture. The granitic types considered in the present study were mostly collected from the Northern region of Portugal. The selection of the granite types was based on mineralogical, textural and structural characteristics. Thus, fine to medium, medium to coarse, and coarse-grained granites were selected (some with porphyritic textures). In addition to these criteria, the presence of planar anisotropies and the weathering condition were also considered.

Granite is a quasi-brittle material that has a disordered internal structure. Its tensile behaviour can be well described by the cohesive crack model proposed initially by Hillerborg et al. [12]. Two constitutive laws are necessary to describe the tensile behaviour of granites. The elastic–plastic stress–strain relationship is valid until the peak load is reached. After the peak there is a softening behaviour at the fracture process zone. The definition of the constitutive laws of the material can be done by direct tensile tests and indirect tensile tests (Brazilian splitting test). Figure 1 shows the typical response of granites under direct tension with the stress-strain diagram until peak (Figure 1a) and the softening branch of the stress vs. crack opening diagram (Figure 1b).The area under this branch defines the fracture energy, $G_f$. The results of the direct tensile tests carried out on granites are used in this work because this test is considered to be more appropriate to characterize the basic failure mechanism of quasi-brittle materials. Details of the experimental tests are given in Figure 2.

Figure 3 shows an example of stress–displacement diagrams corresponding to the LVDTs placed at each side of the specimen. The linear stretch of the stress–displacement diagram is associated with the elastic behaviour of the material, whereas the stable microcracking process is reflected by a nonlinear stretch before the peak stress is reached.

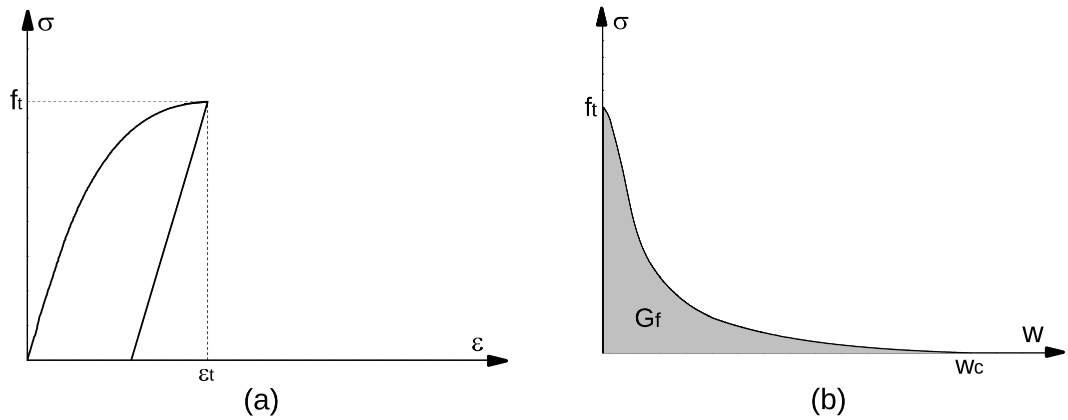
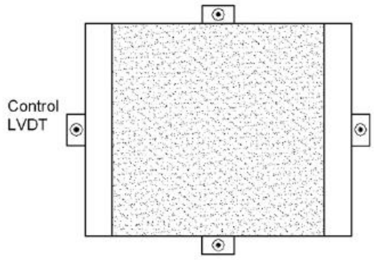


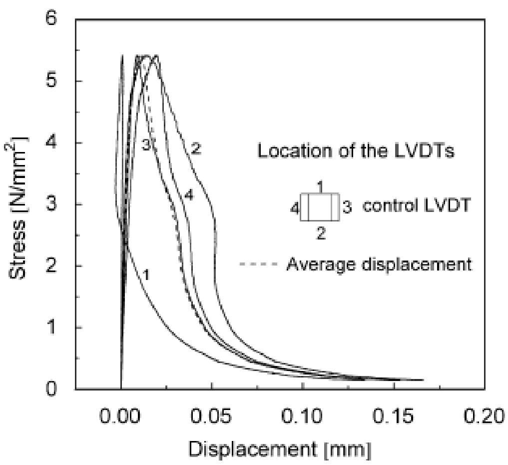

**Figure 1**. Typical response of granites under direct tension: a) stress-strain diagram until peak stress; b) softening branch of the stress vs. crack opening. (Vasconcelos [13])

(a)

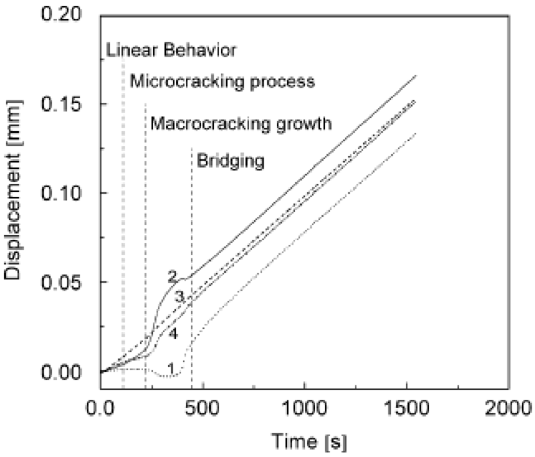



(b)

**Figure 2.** Details of the experimental tests: (a) test setup. (Vasconcelos et al. [13]); (b) view of fracture surface and the location of LVDTs to measure the crack opening




(a)




(b)

**Figure 3**. Typical response of granites under direct tension for a fine to medium-grained, with porphyritic trend, two mica granite: a) stress-displacement diagram at each LVDT; b) evolution of the displacement with time. (Vasconcelos et al. [14])

After this point, macrocracking propagation is established and increasing of the crack opening can be observed with naked eye. This macroscopic fracture process is associated with the steep negative stretch in the softening branch with a slope that depends on the type of granite. Finally, a stress transfer mechanism, due to the bridging effect, appears to be responsible for the long tail of the softening branch. Further details of the performed tests can be found on Vasconcelos et al. [13].

## 3 ARTIFICIAL NEURAL NETWORKS

ANN are intended to be an approximation to the architecture of the human brain. These networks consist of processing units (nodes) interconnected according to a given configuration being the multi-layer perceptron the most popular (Haykin [15]). The nodes are constituted by a set of connections, each associated to a weight, $w_{ij}$ (i and j are neurons or nodes),, that has an excitatory effect for positive values and negative values for inhibition, an integrator (g) that reduces n input arguments (stimuli) to a single value, and an activation function (f) that can introduce a component of non-linearity in the computational process. In our case the network weights are initially randomly generated in the range [-0.7, +0.7], and the f logistic function (1 / (1 + exp (-x)) is used as activation function. Then, the training algorithm is applied adjusting successively the weights, stopping when the slope of the error is approximately zero or after a maximum number of iterations. In the case of regression the forecast is made by summing the contribution of all the activated connections. The general model is given by the following equation (Hastie et al. [16]):

$$\hat{y} = w_{o,0} + \sum_{j=I+1}^{o-1} f\left(\sum_{i=1}^{I} x_i w_{j,i} + w_{j,0}\right) w_{o,i} \quad (1)$$

where $x_i$ are the input parameters or nodes, I is the number of input parameters and o is the output parameter. The predictive capacity of the ANN and MR techniques was tested using only one part of the whole dataset.

This part, corresponding to two-thirds of the whole dataset, was used in an evaluation scheme using 10-fold cross validation. In this scheme nine subsets were used to adjust the model whereas the remaining subset was used to test de model. This process was repeated until all the subsets have been tested and ten runs were performed. After this process the model was fitted using the whole dataset. The one-third of dataset that was not used to fit the model was used to test the model. The evaluation of the predictive capacities of the models was done using the coefficient of correlation of pearson, R, and the root mean square error, RMSE:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)} \quad (2)$$

where $y_i$ is the measured value, $\hat{y}_i$ is the predicted value and N is the number of samples.

An RMSE value closer to zero indicates a better fit whereas higher values of R correspond to better performances. The computing process was performed in the R environment (R Development Core Team [17]) using the RMiner library developed by Cortez [18] that makes easier the use of Data Mining algorithms such as ANN and multiple regressions.

In the next chapters the ANN techniques will be applied to evaluate the parameters defining the tensile-displacement diagrams and to predict the mechanical properties in function of the physical properties. Furthermore multiple regression analysis will also be performed to compare the obtained results.

## 4 PREDICTION OF THE MAIN PROPERTIES THAT CHARACTERIZE THE TENSILE BEHAVIOUR OF THE GRANITES

This section is devoted to the prediction of the key parameters that defining the stress-strain diagram of granites under tensile loading, namely tensile strength, $f_t$, displacement at peak stress, $\delta_{ft}$, and critical crack opening, $w_c$. The ANN and MR models are tested using a single input variable and combinations of two or three variables (UPV, η and ρ). This was done to compare the performance of the models that only use UPV with the performance of models that use other physical parameters with different combinations including or not UPV. Models that use a single input variable are denominated by M1. Models M2 and M3 use two and three input variables, respectively.

The dataset for tensile strength and critical crack opening was composed of 240 registers, whereas for displacement at peak stress the dataset was composed by 251 registers. The general statistical overviews of the rock properties used in databases are presented in Tables 1 and 2.

It can be emphasized that the coefficients of variation of almost all the variables are relatively high. This is related with the wide range of granitic rocks used in this study. It should be stressed that the different mineralogical, textural and structural characteristics, and particularly the distinct weathering state, control the variables employed in this study. When compared to the other variables, the density ρ is less affected by the variability of properties.

**Table 1.** General statistical overview of the rock properties used in database for prediction of $f_c$ and $w_c$

| Symbol | Minimum | Mean | Maximum | Standard Deviation | Coefficient Variation |
|---|---|---|---|---|---|
| UPV (m/s) | 1578.0 | 2851.9 | 4480.6 | 797.7 | 28.0 |
| η(%) | 0.61 | 2.96 | 7.40 | 2.11 | 71.2 |
| ρ (kg/m$^3$) | 2520.6 | 2611.8 | 2704.7 | 45.75 | 1.75 |
| $f_t$ (N/mm$^2$) | 1.28 | 3.38 | 9.04 | 1.61 | 47.8 |
| $w_c$ (mm) | 0.048 | 0.355 | 0.950 | 0.210 | 59.2 |

**Table 2.** General statistical overview of the rock properties used in database for prediction of displacement at peak stress.

| Symbol | Minimum | Mean | Maximum | Standard Deviation | Coefficient Variation |
|---|---|---|---|---|---|
| UPV (m/s) | 1578.01 | 2973.32 | 4577.14 | 851.98 | 28.65 |
| η(%) | 0.41 | 2.70 | 7.42 | 2.18 | 80.74 |
| ρ (kg/m$^3$) | 2452.48 | 2596.11 | 2705.41 | 66.01 | 2.54 |
| $\delta_{ft}$ (mm) | 0.008 | 0.026 | 0.062 | 0.012 | 44.37 |

### 4.1. Prediction of tensile strength

Table 3 shows the best relationships between the tensile strength and the physical parameters using all the dataset and considering unique independent variables, namely *UPV*, $\eta$, and $\rho$. It must be highlighted the good coefficients of correlation obtained when *UPV* and porosity ($\eta$) are used. Nevertheless, the relation between $f_t$ and ρ is the poorest one. Before the construction of the model the groups of data were split into two sets. The training set with two thirds of the groups of the data (160 cases) and the testing set with one third of the groups of data (80 cases).The mean values of the root mean square error (RMSE) and the coefficient of correlation (R) obtained during the training process are presented in Tables 4 and 5 for all models considered.

**Table 3.** Correlation between $f_t$ with other parameters and the corresponding coefficients of correlation (R).

| Correlations | R |
|---|---|
| $f_t = 2 \times 10^{-5} \times UPV^{1.5343}$ | 0.931 |
| $f_t = 4.3935 \times \eta^{-0.461}$ | 0.804 |
| $f_t = 0.0245 \times \rho - 60.723$ | 0.696 |

According to Johnson [19], correlation coefficient values (R) higher than ±0.8 are considered statistically significant at 95% confidence. It can be seen that most of the values presented in Table 5 are greater than 0.8, which confirms the good predictive capacity of the majority of the models. Despite the nonlinear correlations presented in the Table 3 have been obtained with the whole dataset, the values of correlation coefficients obtained from the ANN approaches were higher than 0.8 (Table 5). Notice that in this case, the ANN model is able to better describe the nonlinear relationship between the variables even with less data. Analysing Tables 4 and 5 it can be concluded that ANN gives better results than MR for all the combinations of input parameters. For M1 and M2 models the best results were obtained including UPV. When two input parameters are used the best result isobtained with ANN model that also include the porosity, *η*. Among all the combinations and models, the best performance was obtained with the ANN model using all the input variables. Both the model using only UPV and the best model were fitted with all the training and testing set and the results are graphically presented in Figure 4.

**Table 4.** Mean values of RMSE obtained in the cross-validation scheme for different combination of input parameters.

| | M1 | | | M2 | | | M3 |
|---|---|---|---|---|---|---|---|
| | UPV | η | ρ | UPV&η | η&ρ | UPV&ρ | UPV&η&ρ |
| ANN | 0.5400 | 0.8050 | 1.0065 | 0.4965 | 0.8850 | 0.4294 | 0.4111 |
| MR | 0.6321 | 1.1684 | 1.1827 | 0.6370 | 1.1598 | 0.6235 | 0.6215 |

**Table 5.** Mean values of R obtained in the cross-validation scheme for different combination of input parameters.

| | M1 | | | M2 | | | M3 |
|---|---|---|---|---|---|---|---|
| | UPV | η | ρ | UPV&η | η&ρ | UPV&ρ | UPV&η&ρ |
| ANN | 0.942 | 0.868 | 0.782 | 0.951 | 0.839 | 0.964 | 0.967 |
| MR | 0.920 | 0.687 | 0.678 | 0.918 | 0.693 | 0.922 | 0.922 |

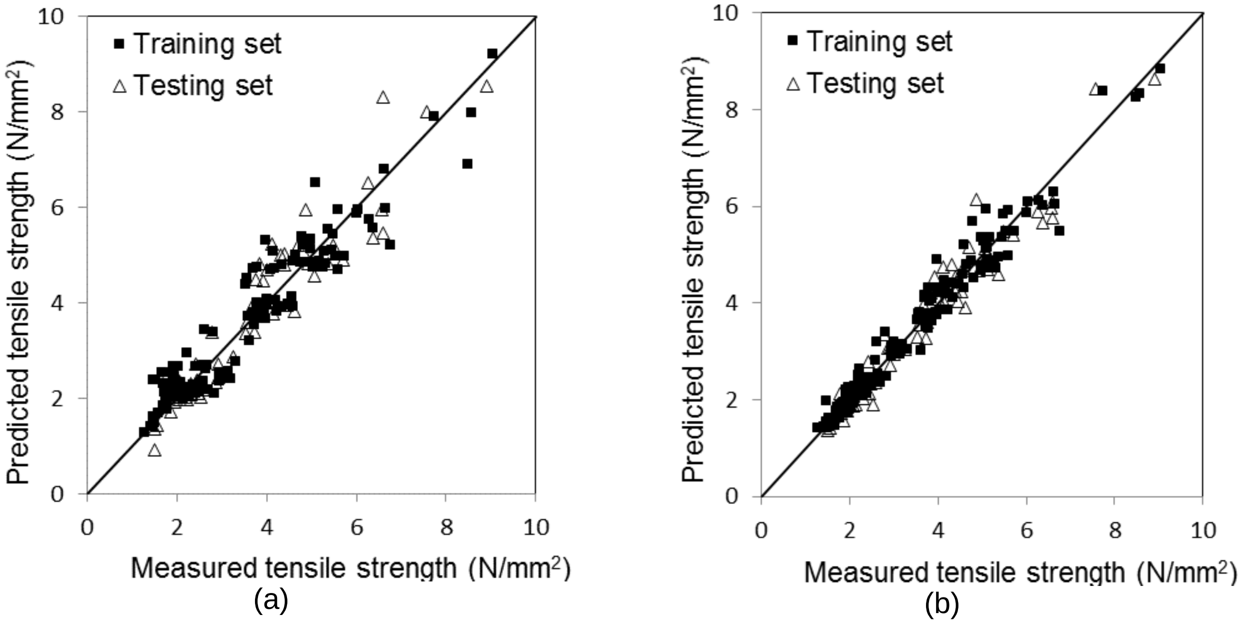



Figure 4. Performance of the ANN model using: (a) only UPV; (b) all the input parameters.

It can be seen that the values obtained with the model based only on UPV are not far away from the measured values, even if it present more variability. However, the best model, based on three input parameters, has the better accuracy to obtain the measured results.

## 4.2. Displacement at peak stress

Table 6 shows the best relationships between the displacement at peak stress, $\delta_{ft}$, and the other parameters using all the dataset. It must be stressed the good coefficients of correlation obtained when UPV and η are used. Nevertheless, the relation between $\delta_{ft}$ and $\rho$ is the poorest one, similarly to what was observed when the tensile strength is predicted.

**Table 6.** Correlations between $\delta_{ft}$ with other parameters and the corresponding coefficients of correlation (R).

| **Correlations** | **R** |
|---|---|
| $\delta_{ft} = 3397.3 \times UPV^{-1.494}$ | 0.911 |
| $\delta_{ft} = 0.0174 \times \eta^{0.4708}$ | 0.896 |
| $\delta_{ft} = -0.0001 \times \rho + 0.3702$ | 0.761 |

Before the construction of the model the groups of data were also split into two sets. The training set with two thirds of the groups of the data (167 cases) and the testing set with one third of the groups of data (84 cases). The mean values of the root mean square error (RMSE) and the coefficient of correlation (R) obtained during the training process are presented in Tables 7 and 8. Despite the correlation presented in the Table 6 have been obtained with the whole dataset the values of correlation coefficients obtained with M1 models from the ANN approaches were higher (Table 8). Notice that also in this case, the ANN model is able to better describe the nonlinear relationship between the variables even with less data.

**Table 7.** Mean values of RMSE obtained in the cross-validation scheme for different combination of input parameters.

| | M1 | | | M2 | | | M3 |
|---|---|---|---|---|---|---|---|
| | UPV | η | ρ | UPV&η | η&ρ | UPV&ρ | UPV&η&ρ |
| ANN | 0.0041 | 0.0047 | 0.0066 | 0.0041 | 0.0059 | 0.0052 | 0.0043 |
| MR | 0.0054 | 0.0067 | 0.0075 | 0.0049 | 0.0068 | 0.0050 | 0.0049 |

**Table 8.** Mean values of R obtained in the cross-validation scheme for different combination of input parameters.

| | M1 | | | M2 | | | M3 |
|---|---|---|---|---|---|---|---|
| | UPV | η | ρ | UPV&η | η&ρ | UPV&ρ | UPV&η&ρ |
| ANN | 0.931 | 0.911 | 0.817 | 0.933 | 0.862 | 0.898 | 0.926 |
| MR | 0.880 | 0.808 | 0.752 | 0.904 | 0.805 | 0.897 | 0.904 |

From the analysis of Tables 7 and 8 it can be seen that ANN give the best results for all the combinations of input parameters. This confirms the nonlinear relationships between $\delta_{ft}$ with the other parameters. The best performance is obtained using only *UPV* or *UPV* with $\eta$. These models were fitted with all the training and testing set and the result are graphically presented in Figure 5. It can be seen that both models perform similarly and have a great accuracy to obtain the measured results.

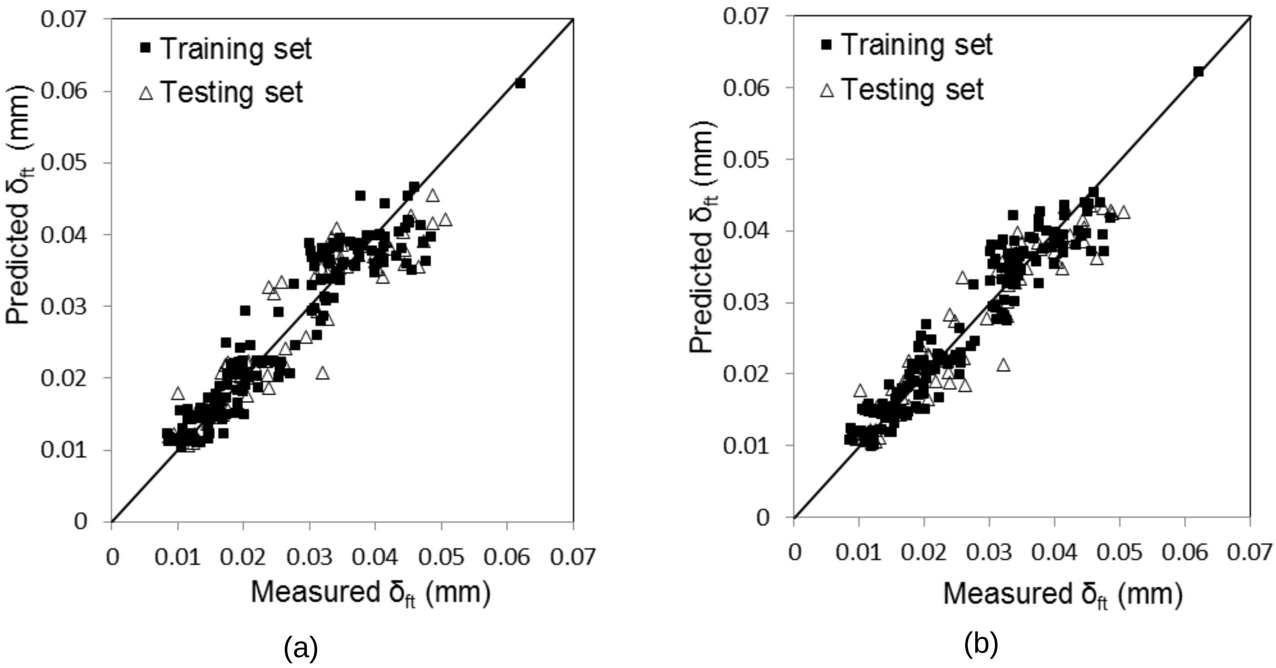



**Figure 5.** Performance of the ANN model using: a) only UPV; b) UPV and η.

### 4.3. Critical crack opening

Comparing the coefficients of correlation presented in Table 9 with those obtained using the ANN models with one input variable it can be seen that only the coefficient of correlation obtained with ρ is better using the ANN model. However, the correlation presented in the Table 9 has been obtained with the whole dataset.

**Table 9.** Correlations between $w_c$ with other parameters and the corresponding coefficients of correlation (R).

| Correlations | R |
|---|---|
| $w_c = 2.0449 \times exp(-7 \times 10^{-4} \times UPV)$ | 0.847 |
| $w_c = 0.1729 \times \eta^{0.6632}$ | 0.815 |
| $w_c = 1 \times 10^{10} \times e^{-0.009.\rho}$ | 0.670 |

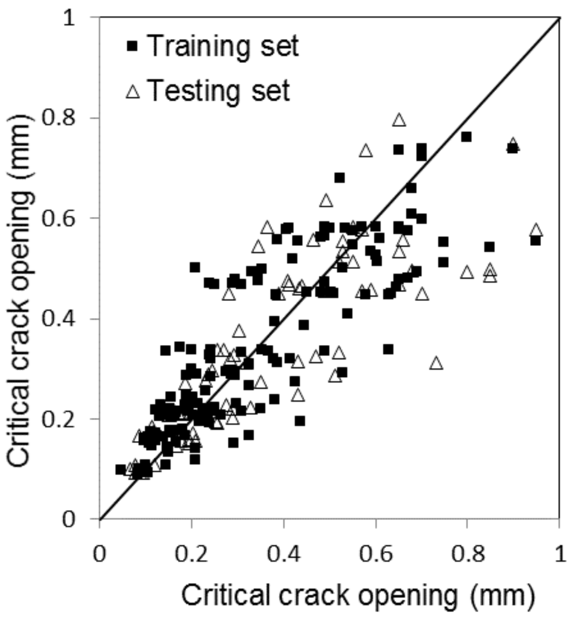
From the analysis of Tables 10 and 11 it can be seen that ANN is clearly better than MR for all the combinations of input parameters. This confirms the nonlinear relationships between $w_c$ with other parameters. The best performance is obtained using all the input parameters, even if only very slight improvements were obtained. Furthermore, the best results using one or two input parameters are obtained with $\eta$. The best model was fitted with all the training and testing set and the result is graphically presented in Figure 6. It can be seen that there is a considerable scatter around the 45 degree line but the prediction remain significant when ANN is considered.

**Table 10.** Mean values of RMSE obtained in the cross-validation scheme for different combination of input parameters.

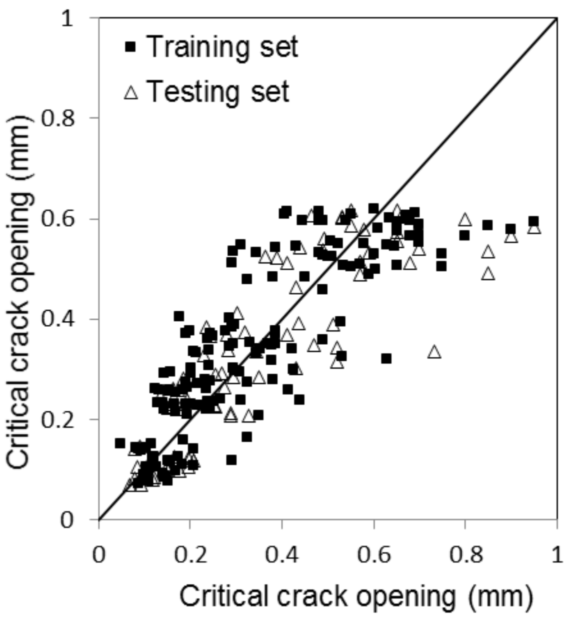
| | M1 | | | M2 | | | M3 |
|---|---|---|---|---|---|---|---|
| | UPV | η | ρ | UPV&η | η&ρ | UPV&ρ | UPV&η&ρ |
| ANN | 0.1196 | 0.1193 | 0.1435 | 0.1153 | 0.1136 | 0.1156 | 0.1133 |
| MR | 0.1334 | 0.1310 | 0.1586 | 0.1178 | 0.1283 | 0.1307 | 0.1138 |

**Table 11.** Mean values of R obtained in the cross-validation scheme for different combination of input parameters.

| | M1 | | | M2 | | | M3 |
|---|---|---|---|---|---|---|---|
| | UPV | η | ρ | UPV&η | η&ρ | UPV&ρ | UPV&η&ρ |
| ANN | 0.810 | 0.812 | 0.717 | 0.827 | 0.833 | 0.826 | 0.836 |
| MR | 0.755 | 0.765 | 0.627 | 0.815 | 0.776 | 0.767 | 0.829 |




(a)




(b)

**Figure 6**. Performance of the ANN model using: (a) only UPV; (b) all the input parameters.

## 5 CONCLUSIONS

This paper deals with the prediction of the main parameters describing the complete tensile behaviour of granites under direct tensile testing, namely tensile strength, displacement at peak stress and critical crack opening parameters using ANN and MR. Both models consider the UPV alone and combined with more one or two physical parameters. Single and Multiple regression analyses were also performed. The best single relationships between the predicted parameters and UPV are nonlinear. Therefore, it is not surprising that the ANN models have given better results than the MR models. The tensile strength and the displacement peak stress were well predicted by the ANN models using UPV alone, even if the more accurate prediction would be obtained using UPV with porosity and density for the tensile strength and using UPV with porosity for the displacement at peak stress. However, if only the UPV is available very reasonable prediction can be achieved.

The results for the prediction of the critical crack opening are considerably poorer, which should be related to the more scatter found for this variable. However, if ANN is used all the prediction trials are significant and one more time the UPV can give reasonable predictions.

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